Derivative-based solution of the optimization problem(s) in DeMarco's model

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August 5, 2014

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Cascading Network Failure

 To predict cascading failure in large-scale networks, solid understanding of propagations of failures in small-scale networks is vital.



Cascading Network Failure

- To predict cascading failure in large-scale networks, solid understanding of propagations of failures in small-scale networks is vital.
- This allows optimal redistribution of loads and network design.

Network Model(s): I

- Eight-node, Eleven-branch circuit is used as a toy model.
- Model state

$$\mathbf{x} = egin{bmatrix} \phi \ \mathbf{q} \ \gamma \end{bmatrix} \in \mathbb{R}^{26}$$
 (1)

where

- 1) ϕ is a vector of nodal flux differences ($\phi \in \mathbb{R}^7$),
- 2) **q** is the vector of nodal charges on capacitors ($\mathbf{q} \in \mathbb{R}^8$),
- 3) γ is the failure state of branches ($\gamma \in \mathbb{R}^{11}$),

Network Model(s): II

DeMarco's original model equations

$$d\phi = E_r^T C^{-1} \mathbf{q} \ dt \tag{2}$$

$$d\mathbf{q} = \left(-E_r H_r L^{-1} H_r^T \phi - G C^{-1} \mathbf{q} + i_{\text{in}}\right) dt, \tag{3}$$

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Stochastic Version of the model

$$\begin{bmatrix} d\phi \\ dq \end{bmatrix} = \mathbf{M} + \mathbf{P} + \mathbf{U}$$

$$= \begin{bmatrix} E_r^T C^{-1} \mathbf{q}(t) dt \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ -E_r H_r L^{-1} H_r^T \phi(t) dt \end{bmatrix} + \begin{bmatrix} 0 \\ -GC^{-1} \mathbf{q}(t) dt + \sqrt{2G\tau} \ dW_t \end{bmatrix}.$$
(4)

- $i_{\rm in}$: the current input, τ : system's temperature,
- C, E_r , H_r , L, G: constant matrices,
- M, P, U: system's mass, potential, Ornstein Uhlenbeck process.

Time stepping: A Splitting Solver

The integrator is a composition of maps

$$\begin{bmatrix} \phi(t) \\ \mathbf{q}(t) \end{bmatrix} = \mathbf{P}_{\frac{t}{2}} \circ \mathbf{M}_{\frac{t}{2}} \circ \mathbf{U}_{t} \circ \mathbf{M}_{\frac{t}{2}} \circ \mathbf{P}_{\frac{t}{2}} \left(\begin{bmatrix} \phi(0) \\ \mathbf{q}(0) \end{bmatrix} \right); \tag{5}$$

$$\mathbf{M}_t \left(\begin{bmatrix} \phi(0) \\ \mathbf{q}(0) \end{bmatrix} \right) = \begin{bmatrix} \phi(0) + E_r^T C^{-1} \mathbf{q}(0) t \\ \mathbf{q}(0) \end{bmatrix}, \tag{6}$$

$$\mathbf{P}_{t}\left(\begin{bmatrix}\phi(0)\\\mathbf{q}(0)\end{bmatrix}\right) = \begin{bmatrix}\phi(0)\\\mathbf{q}(0) - E_{r}H_{r}L^{-1}H_{r}^{T}\phi(0)t\end{bmatrix},\tag{7}$$

$$\mathbf{U}_{t}\left(\begin{bmatrix}\phi(0)\\\mathbf{q}(0)\end{bmatrix}\right) = \begin{bmatrix}\phi(0)\\e^{-GC^{-1}t}\mathbf{q}(0) + \sqrt{\tau C\left(I - e^{-2GC^{-1}t}\right)}\mathbf{d}\end{bmatrix}, \tag{8}$$

Where t is the step size, and \mathbf{d} is the stochastic force.



Optimization problems

Since we are interested in failure, we ask how the white noise might steer the system towards increasing energy.

• The exact problem:

$$\min_{\mathbf{d}_1, \mathbf{d}_2, \dots, \mathbf{d}_N} \mathcal{J}(\mathbf{d}_1, \mathbf{d}_2, \dots, \mathbf{d}_N) = \sum_{i=1}^N \mathbf{d}_i^T \mathbf{d}_i$$
 (9)

subject to

$$\max(E_N) > \epsilon. \tag{10}$$

Solving the exact problem requires solving one optimization problem for each line.

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• A proxy problem: replace constraint with:

$$\mathbb{I}_{N}^{T} E_{N} > \epsilon, \quad (\text{Or } E_{N}^{T} E_{N} > \epsilon) \tag{11}$$

where E_N is the energy function, and \mathbb{I}_N is a vector of all ones.



Energy Function

$$E_{N}(\phi_{N}) = E_{N} \begin{pmatrix} \begin{bmatrix} (\phi_{N})_{1} \\ (\phi_{N})_{2} \\ (\phi_{N})_{3} \\ (\phi_{N})_{4} \\ (\phi_{N})_{5} \\ (\phi_{N})_{7} \end{bmatrix} \end{pmatrix} = \begin{pmatrix} \frac{1}{2}L_{1}^{-1}\gamma_{1}\left(-(\phi_{N})_{1}\right)^{2} \\ \frac{1}{2}L_{2}^{-1}\gamma_{2}\left(-(\phi_{N})_{2}\right)^{2} \\ \frac{1}{2}L_{3}^{-1}\gamma_{3}\left((\phi_{N})_{2} - (\phi_{N})_{3}\right)^{2} \\ \frac{1}{2}L_{4}^{-1}\gamma_{4}\left((\phi_{N})_{1} - (\phi_{N})_{3}\right)^{2} \\ \frac{1}{2}L_{5}^{-1}\gamma_{5}\left((\phi_{N})_{3} - (\phi_{N})_{4}\right)^{2} \\ \frac{1}{2}L_{6}^{-1}\gamma_{6}\left((\phi_{N})_{3} - (\phi_{N})_{5}\right)^{2} \\ \frac{1}{2}L_{7}^{-1}\gamma_{7}\left((\phi_{N})_{1} - (\phi_{N})_{5}\right)^{2} \\ \frac{1}{2}L_{8}^{-1}\gamma_{8}\left((\phi_{N})_{4} - (\phi_{N})_{5}\right)^{2} \\ \frac{1}{2}L_{9}^{-1}\gamma_{9}\left((\phi_{N})_{4} - (\phi_{N})_{7}\right)^{2} \\ \frac{1}{2}L_{10}^{-1}\gamma_{10}\left((\phi_{N})_{5} - (\phi_{N})_{6}\right)^{2} \\ \frac{1}{2}L_{11}^{-1}\gamma_{11}\left((\phi_{N})_{6} - (\phi_{N})_{7}\right)^{2} \end{pmatrix}$$

$$(12)$$

Probability of Failure(s)

We can compute the probability of one failure (at time t_N) from optimal noise vectors $\mathbf{d}_1, \mathbf{d}_1, \dots \mathbf{d}_N$ via

$$P(\mathsf{Failure}|\mathbf{d}_1, \mathbf{d}_1, \dots \mathbf{d}_N) = e^{-\frac{\sum_{i=1}^N \mathbf{d}_i^T \mathbf{d}_i}{\tau}}$$
(13)

Multiple failure is an enumeration problem solved by exhaustive search.



Derivative Information: I

We have reformulated the splitting solver as linear discrete map:

$$\mathbf{x}_i = \mathbf{A}\mathbf{x}_{i-1} + \mathbf{B}\mathbf{d}_i, \tag{14}$$

The blocks of **A** are:

$$\mathbf{A}_{1,1} = I + (E_r^T C^{-1})(I + e^{-GC^{-1}h})(-E_r H_r L^{-1} H_r^T)(\frac{h^2}{4})$$
 (15)

$$\mathbf{A}_{1,2} = (E_r^T C^{-1})(I + e^{-GC^{-1}h})(\frac{h}{2})$$
 (16)

$$\mathbf{A}_{2,1} = \left((-E_r H_r L^{-1} H_r^T) (E_r^T C^{-1}) (\frac{h^2}{4}) + I \right) (I + e^{-GC^{-1}h}) (-E_r H_r L^{-1} H_r^T) (\frac{h}{2})$$
 (17)

$$\mathbf{A}_{2,2} = (-E_r H_r L^{-1} H_r^T) (E_r^T C^{-1}) (I + e^{-GC^{-1}h}) (\frac{h^2}{4}) + (e^{-GC^{-1}h})$$
(18)

$$\mathbf{A}_{1,3} = \mathbf{A}_{2,3} = \mathbf{A}_{3,1} = \mathbf{A}_{3,2} = \mathbf{0}; \ \mathbf{A}_{3,3} = I$$
 (19)

Derivative Information: II

B reads

$$\mathbf{B} = \begin{bmatrix} (E_r^T C^{-1}) \sqrt{\tau C (I - e^{-2GC^{-1}h}) (\frac{h}{2})} \\ ((-E_r H_r L^{-1} H_r^T) (E_r^T C^{-1}) (\frac{h^2}{4}) + I) \sqrt{\tau C (I - e^{-2GC^{-1}h})} \\ \mathbf{0} \end{bmatrix}$$
(20)

the derivatives read

$$\nabla_{\mathbf{x}_{i-k}}\mathbf{x}_{i} = \mathbf{A}^{k} \quad \forall k = 1, 2, \dots, i-1 \tag{21}$$

$$\nabla_{\mathbf{d}_{i-k}} \mathbf{x}_i = \mathbf{A}^k B \quad \forall k = 0, 1, \dots, i-1$$
 (22)

$$\nabla_{\mathbf{d}_{i}} E_{N} = (\nabla_{\phi_{N}} E_{N})(\nabla_{\mathbf{d}_{i}} \phi_{N})$$

$$= (E_{N\phi})(\nabla_{\mathbf{d}_{i}} \phi_{N}) \quad \forall i = 1, 2, \dots, N$$
(23)

 $E_{N\phi} = \frac{dE_N}{d\phi_N} \in \mathbb{R}^{11 \times 7}$ is the Jacobian of the energy functional w.r.t flux differences.

Derivative Information: III

• Gradient of the cost function:

$$\nabla_{\begin{bmatrix} \mathbf{d}_{1}^{T}, \mathbf{d}_{2}^{T}, \dots, \mathbf{d}_{N}^{T} \end{bmatrix}^{T}} \mathcal{J} = 2 \begin{bmatrix} \mathbf{d}_{1} \\ \mathbf{d}_{2} \\ \mathbf{d}_{3} \\ \vdots \\ \mathbf{d}_{N} \end{bmatrix} . \tag{24}$$

Gradient of the constraint(s):

$$\nabla_{\phi_{N}}(\mathbb{I}_{N}^{T}E_{N}) = E_{N\phi}^{T}\mathbb{I}_{N}; \quad \nabla_{\phi_{N}}(E_{N}^{T}E_{N}) = 2\begin{bmatrix} (\nabla_{\mathbf{d}_{1}}E_{N})^{T}E_{N} \\ (\nabla_{\mathbf{d}_{2}}E_{N})^{T}E_{N} \\ \vdots \\ (\nabla_{\mathbf{d}_{N}}E_{N})^{T}E_{N} \end{bmatrix}$$

$$(25)$$

Results I: Probability of failure(s)

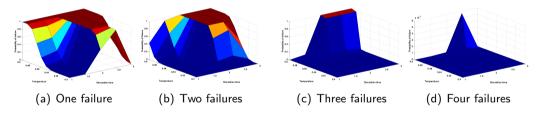


Figure: Probability of line failure(s). One, two, three, and four failures are plotted.

Results III: Probability of failure(s)

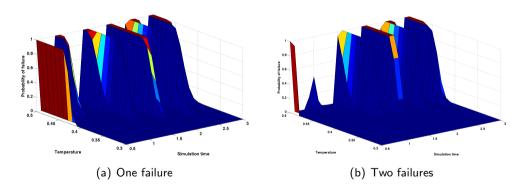


Figure: Probability of line failure(s) on higher resolution grid



Results IV: Probability of failure(s)

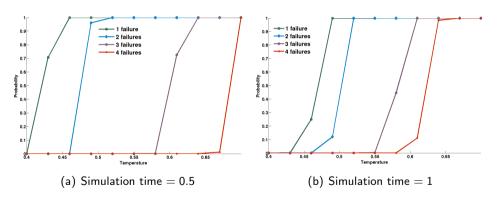


Figure: Relation between probability of branch failures and system's temperature.



Results V: Computational Time

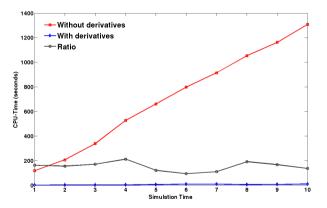


Figure: CPU-time of the optimization step for one failure case with and without derivative information.

Thanks

Questions?

